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Adaptation with climate uncertainty: An examination of agricultural land use in the United States

Jianhong E. Mu[a,*], Bruce A. McCarl[a], Benjamin Sleeter[b], John T. Abatzoglou[c], Hongliang Zhang[d]

[a] Department of Agricultural Economics, Texas A&M Unsiversity, College Station, TX, 77840, United States
[b] U.S. Geological Survey, Menlo Park, CA, 94025, United States
[c] Department of Geography, University of Idaho, Moscow, ID, 83844, United States
[d] Department of Economics and Business, University of Neuchâtel, 2000, Neuchâtel, Switzerland

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ABSTRACT

This paper examines adaptation responses to climate change through adjustment of agricultural land use. The climate drivers we examine are changes in long-term climate normals (e.g., 10-year moving averages) and changes in inter-annual climate variability. Using US county level data over 1982 to 2012 from Census of Agriculture, we find that impacts of long-term climate normals are as important as that of inter-annual climate variability. Projecting into the future, we find projected climate change will lead to an expansion in crop land share across the northern and interior western United States with decreases in the south. We also find that grazing land share increases in southern regions and Inland Pacific Northwest and declines in the northern areas. However, the extent to which the adaptation potential would be is dependent on the climate model, emission scenario and time horizon under consideration.

1. Introduction

Farming by its very nature is adaptive to climate. Today given the rapid pace of climate change adaptation is occurring throughout the landscape. There are two types of land allocation decisions that farmers can make to cope with climate change, including short-run allocations associated with management of a particular type of system due to effects of inter-annual climate variability and long-run allocations associated with investment decisions that involve choices between different types of systems due to effects of long-term climate normals. Hsiang (2016) referred the former as the direct effect and the latter as the belief effect and the interactions between beliefs and direct impacts and belief effects themselves as adaptations.

Many studies have examined land-use with or without the consequences of climate using econometric or structure models (Adams et al., 1990; Cho and McCarl, 2017; Haim et al., 2011; Lubowski et al., 2006; Lubowski, 2008; Lubowski and Roberts, 2008; Miao et al., 2015; Mu et al., 2013, 2017; Mu et al., 2015; Reilly et al., 2003; Wu et al., 2004). In these studies, both long-term and short-term variability phenomena have been examined as potential drivers of land use change. In particular, Cho and McCarl (2017) investigated the direct effects of inter-annual climate variability on crop-mix shift and Mu et al. (2013) examined the belief effects of changes in 3-year average climate normals on land use change between crop and pasture. In addition, Mu et al. (2017) used a two-stage approach to reveal direct effect of inter-annual climate variability on land use net returns and measure adaptation as shifts of land use shares to respond to thirty-year climate characteristics.

As argued by Kelly et al. (2005), long-term shifts in regional climate characteristics determine basic crop choice and land-use patterns while actual weather (inter-annual climate variability) determines actual profits. Thus, impacts of long-term climate normals should be a fundamental driver in the choice of major enterprise characteristics and is likely more important than short run climate fluctuations (Deschenes and Kolstad, 2011; Kelly et al., 2005; Mendelsohn et al., 2007). However, inter-annual climate variability may also be very important with the incidence of droughts, heat waves etc. In this regard, it is important to consider both long-term climate normals and inter-annual climate variability when trying to understand crop mix and land-use patterns. In fact, Deschenes and Greenstone (2007) and Mendelsohn et al. (2007) both suggest that omitting these factors could lead to biased estimates of climate impacts.

Another focus in climate change assessments that has been received increasingly attentions is consideration of the full range of variability in long-term climate projections. In particular, numerous Earth System Models (ESMs) are now being used by the climate science community in

* Corresponding author.
E-mail address: mujh@tamu.edu (J.E. Mu).

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making climate change projections.[1] The use of these many models leads to a distribution of projections with no real global basis for picking the most likely outcomes (Flato et al., 2013; Randall et al., 2007). However, virtually all land use related studies have used only a selected few projections without accounting for the full range of the existing projections (Burke et al., 2015). Burke et al. (2015) argue that estimates of climate impacts from a limited set of ESMs is likely misleading and possibly biased.

In the face of these prior studies, this study attempts to examine land-use change but in a setting where two contributions are made. First, we distinguish farmers' adaptive responses in terms of land-use to inter-annual climate variability and longer-term climate shifts in mean climate characteristics. Second, within the context of alternative climate forcing scenarios, we develop more broadly-based distributions of future land use constructed across the full set of climate model projections from the Coupled Model Intercomparison Project Phase 5 (CMIP5).

2. Methods

Theoretically, inter-annual climate variability can affect land use choices where management of farm income variability leads one to alter land use to less risky patterns, while shifts in long term climate normals lead one to choices of different enterprises that are better suited to different average climate regimes (Mu et al., 2017). Particularly, our analysis is based on the observation that farmers make two types of land allocation decisions: (1) changes in short run bio-physical or socio-economic conditions give rise to adjustments in management decisions that are low-cost and are typically made in each production period subject to the constraints imposed by a particular system; (2) changes in long run bio-physical and socio-economic conditions and changes in technology and policy may lead to more fundamental and non-marginal changes in the production system that involve substantial adjustment costs or capital investments. These two adjustments together cause shifts from cereals to other crops or pasture, or from crop to livestock production, or from dairy to meat production.

To investigate changes in land use shares as the adaptive response to inter-annual climate variability and longer-term climate normals, we will project the probability of land being used in different ways as a function of variables describing these climate phenomena. In particular, we will use a Fractional Multinomial Logit (FMLOGIT) model following the work of Mu et al. (2013) and Cho and McCarl (2017). The analysis will be done considering the uses of crop land, other cropland, grazing land and woodland as they are spread across the landscape using county-level agricultural census data for the Contiguous United States from 1982 to 2012. Here, inter-annual climate variability is the individual observation for a given year in a specific location. Long-term climate normals are expressed by taking long-term average of climate measures over a certain period, such as 10 years. The econometric form of the FMLOGIT model is:

$$E\left(y_{jit} \middle| X, W, \overline{Z}\right) = \frac{\exp(X_{it}\theta_j + \sum_K \beta_{jk} W_{kit} + T_{it}\gamma_j + \overline{Z_i}\varphi_j)}{\sum_J \exp(X_{it}\theta_j + \sum_K \beta_{jk} W_{kit} + T_{it}\gamma_j + \overline{Z_i}\varphi_j)} \ldots \text{for all } j \tag{1}$$

where y_{jit} is the land use share for usage type j in county i at time t and is the proportion of the land that is of total land in that county and thus falls between zero and one. The alternative land usages considered (j) include usage in cropping, other cropland use, grazing and woodland. The variables of interest are in W_{kit} and the "k" index simply denotes the various climate measures we control for. For example, ten-year average growing season degree-days and total precipitation and their squared terms, ten-year average precipitation intensity index, along annual total precipitation, degree-days and their squared terms, precipitation intensity and drought index. We use X_{it} to control for other factors, which are soil conditions, county centroid latitude, irrigation share, annualized revenue-cost ratios that we constructed for crop and livestock based on the total sales of crop and livestock products and total production expenses, amount of government payments per acre, and population density. T_{it} is the time trend, and θ, β, φ and γ are parameters to be estimated.

In Eq. (1), we also include the vector of $\overline{Z_i}$, which is a subset of the explanatory variables that is averaged over time for each county i. Specifically, we include the average of the annualized revenue-cost ratios, population density and irrigation shares that are possibly affected by land-use policies or farm management decisions.[2] There are two reasons to include $\overline{Z_i}$ in Eq. (1). First, the possible endogeneity problem may raise in the estimation with socio-economic variables.[3] For example, the annualized revenue-cost ratios based on observed revenues and costs may be biased due to unobservable effects in the error terms within the land use share equation. Also, the share of land with irrigation could be affected by unobservable factors that also affect land allocation. Second, there is a practical obstacle to incorporate panel model fixed-effects when estimating a nonlinear model, which relates to the difficulty of estimating nonlinear models with possibly thousands of dummy variable coefficients (Greene et al., 2002). To solve the possible endogeneity problem and conquer the difficulty of including fixed effects in the FMLOGIT model, we apply the correlated random effects or Chamberlain-Mundlak approach when estimating Eq. (1). This approach requires the assumption that a proportion of the explanatory variables are correlated with the unobservables. Using this approach, the fixed effects estimator can be computed as a pooled estimator using the original data, but adding the time averages of covariates as additional explanatory variables (Wooldridge, 2009).

3. Data sources and variables

Table 1 presents statistical summaries of selected items within the data set including agricultural land use shares, annualized revenue-cost ratios, inter-annual climate variability measures and long-term climate characteristics in the United States using county level data from 1982 to 2012.[4] All dollar values are adjusted to year 2007 dollars.

3.1. Agricultural land use

County-level agricultural land for cropping, grazing, other cropland use and woodland use were obtained from the Census of Agriculture for the census years 1982, 1987, 1992, 1997, 2002, 2007 and 2012 for the Contiguous United States. To avoid double counting, we reclassified land uses in the Census of Agriculture to correspond to agricultural systems defined in this paper:

(1) *Cropland:* harvested cropland;

(2) *Other Cropland:* idle cropland, land with failed crops, cover crops, summer fallow and land enrolled in conservation reserve, wetlands reserve, farmable wetlands, or conservation reserve enhancement programs;

(3) *Grazing land:* cropland for pasture, which could be used for crop production with soil improvement, and land used for permanent pasture and rangeland, and woodland for pasture, mainly for grass and other forage production;

[1] There are 20 climate models from the Coupled Model Inter-comparison Project Phase 5 (CMIP5)

[2] Although weather variables have both time and space variation, they are assumed orthogonal to the unobservables, thus are not included in $\overline{Z_i}$.

[3] The reversed causality due to the mitigation effects of agriculture for climate change is not a major concern here because we focus on farmland re-allocation among crop, other crops, grazing land and woodland. Mainly the land use change with the conversion of forests to agricultural land could involve massive greenhouse emissions and contribute to global warming (Popp et al. 2014). However, forest land is not considered in this analysis.

[4] Please note that our panel data are from Census of Agriculture with year gaps, there is no need to perform the panel unit root test because stationarity is not a concern here.

Table 1
Variable descriptions and statistics.

Variables	Mean	Std. Dev.	Min	Max
Non-climate variables				
Total cropland (thousand acres)	100.83	114.23	0	1187.38
Total rangeland (thousand acres)	136.70	302.00	0	7329.41
Total other crop land (thousand acres)	26.82	54.91	0	1010.43
Total woodland (thousand acres)	14.50	15.00	0	195.31
Share of crop land	0.41	0.26	0	1
Share of grazing land	0.38	0.27	0	1
Share of other crop land	0.08	0.07	0	1
Share of wood land	0.13	0.14	0	0.87
Share of land in irrigation	0.05	0.11	0	1
Annualized revenue-cost ratios of crop products	2.50	7.51	0	348.45
Annualized revenue-cost ratios of livestock products	4.03	5.61	0	141.70
Annualized government payments per acre (thousand $ in 2007 value)	0.02	0.02	0	0.55
Population density, person per 100 square mile of land areas	1.83	11.74	0	481.26
Latitude	38.28	4.84	25.60	48.84
Weather and climate variables				
Inter-annual total precipitation (m)	10.01	4.04	0	42.01
Inter-annual total degree-days with temperature between 8 °C and 32 °C (thousand)	2.61	1.04	0	6.15
Inter-annual precipitation intensity index	0.21	0.09	0	0.67
Drought index	0.18	0.39	0	1
Long-term total precipitation (m), 10-year moving averages	9.77	3.62	0	33.15
Long-term total degree-days with temperature between 8 °C and 32 °C (thousand), 10-year moving averages	2.55	1.02	0	6.03
Long-term precipitation intensity index, 10-year moving averages	0.21	0.04	0.02	0.41
Soil characteristics				
Fraction clay	0.18	0.21	0	1
Fraction sand	0.09	0.19	0	1
Fraction flood-prone	0.15	0.18	0	1
K-Fact	0.30	0.06	0.01	0.55
Slop length	218.43	141.07	20	1649
Permeability	2.89	2.45	0.03	20
Wetlands	0.10	0.10	0	0.82
Moisture capacity	0.17	0.03	0.04	0.33
Salinity	0.01	0.04	0	0.76

Note: mean values are calculated for a total sample from 1982 to 2012. Total land of crop, grazing, other crop and wood uses is used to calculate the land-use shares.

(4) *Woodland*: woodland not used for pasture.

On average, 41% of total agricultural land is used for crop production, 8% of land is for other cropland use, 38% of land is used for grazing, and 13% of land is used as wood and bushes.

3.2. Annualized revenue-cost ratios

To calculate the revenue-cost ratios and per acre government payment, we obtained sales of livestock and crop products, government payments and total production expenses from the U.S. Bureau of Economic Analysis. We define the average cost per acre in county i at census year t as c_{it} and the average revenue per acre as r_{hit} for h = crop and livestock. It follows that the revenue-cost ratios for activity h is $\frac{r_{hit}}{c_{it}}$. Per acre production cost is the total production cost divided by the total of crop, grazing and other cropland. Per acre crop (livestock) sale is the total crop (livestock) sales divided by the total of crop and other cropland (total grazing land). We then take the ratio of the per acre sale and the per acre cost to compute the revenue-cost ratios for crop and grazing land, respectively. We use the per acre government payment as the revenue-cost ratio for other cropland, which is the total government payment divided by the total of crop, grazing and other cropland.

We then further to construct the annualized revenue-costs ratios because farmers make land-use decisions upon their expectations of long-run operating profits plus government payments that are discounted over a time horizon. In order to do this, we include two earlier years of agricultural land uses, agriculture product sales, costs and government payments, e.g., 1974 and 1978, as additional data to compute the average of every two-census years' revenue-cost ratios and per acre government payments. For example, we use the average of 1974 and 1978 as the annualized revenue-cost ratios and per acre government payment for year 1982 and the average of 1978 and 1982 for year 1987 and so on so forth.

3.3. Historical weather and climate data

As mentioned earlier, inter-annual climate variability is defined as the individual observation for a given year and long-term climate characteristics are defined as the ten-year moving averages of these observations. Historical weather observations were obtained by aggregating gridded ~4-km spatial resolution surface meteorological datasets from Abatzoglou (2013) to the county level. Inter-annual climate variability includes annual total precipitation, growing season degree-days and their squared terms, precipitation intensity and drought index. We use one-year lagged weather variables instead of using the current period ones to account for the inter-annual climate variability because several previous studies have suggested that farmers usually use previous year weather information or the weather information just before planting to make their land use decision, particularly for crop uses (Miao et al., 2015).

Precipitation intensity was defined as the fraction of annual total precipitation occurring in days exceeding the 95th percentile of the climatological distribution for wet days (Tebaldi et al., 2006). We convert daily temperatures into degree-days with the lower threshold equal to 8 °C and the upper threshold to 32 °C and sum over a year as the growing season. The drought index is a binary measure based on the growing season Palmer Drought Severity Index (PDSI), whereby the drought index equals one if the PDSI ≤ -2 and zero otherwise.[5]

Long-term climate normals include ten-year moving averages of total precipitation and degree-days and their squared terms to capture the trend as well as the nonlinear effects on land uses. We also include ten-year moving average of the precipitation intensity index.

3.4. Other control variables

Data on other control variables (soil conditions, irrigation shares, population density and latitudes) were obtained from several sources. Soil characteristics data were drawn from the National Resource Inventory (NRI) and the data on irrigation share were from the Census of Agriculture. To control demand side effects that may lead to conversion of agricultural land to other non-agricultural use such as urban development, we include population density from U.S. Bureau of Economic Analysis. Latitude is also included to represent the spatial variation of county-level agricultural land uses.

4. Estimation results and robustness checks

Using Eq. (1), four land use systems (crop, grazing, other crop and woodland) are considered in the econometric model and the share of woodland is used as the base case.[6] The full estimation results can be found in Table A1 in the appendix. To better understand estimation results of the FMLOGIT model, we calculate the average partial effects

[5] Using the constructed drought index rather than the PDSI will be easier to interpret its effects on farm outcomes. Because PDSI ranges from -10 (very dry) to 10 (vey wet), and farmers may care more about drought incidences rather than wet conditions.

[6] Results of woodland are omitted because its economic meaning is negligible, however, we can derive estimated effects by using the adding-up constraints.

Table 2
Average partial effects of estimated results using long-term climate normals from 10-year moving averages.

	Eq. (1)			Eq. (1) without climate variables			Eq. (1) without weather variables		
Variables	Share of cropland	Share of other crop land	Share of grazing land	Share of cropland	Share of other cropland	Share of grazing land	Share of cropland	Share of other cropland	Share of grazing land
Annualized revenue-cost ratios of crop products	0.0093*** (0.0012)	−0.0035*** (0.0008)	−0.0032*** (0.0009)	0.0097*** (0.0012)	−0.0042*** (0.0009)	−0.0038*** (0.0009)	0.0089*** (0.0011)	−0.0046*** (0.0009)	−0.0034*** (0.0009)
Annualized revenue-cost ratios of livestock products	−0.0028 (0.0026)	−0.0021*** (0.0005)	0.0055* (0.0032)	−0.0019 (0.0029)	−0.0025*** (0.0006)	0.0046 (0.0035)	−0.0036 (0.0025)	−0.0028*** (0.0005)	0.0062** (0.0029)
Annualized government payments	0.2473*** (0.0921)	0.0062 (0.0229)	−0.3403*** (0.1023)	0.2827*** (0.0887)	0.0011 (0.0235)	−0.2683*** (0.1022)	0.4116*** (0.0896)	0.0325 (0.0230)	−0.4741*** (0.1007)
Population density	0.0161*** (0.0038)	−0.0097*** (0.0016)	−0.0014 (0.0034)	0.0178*** (0.0039)	−0.0108*** (0.0016)	−0.0028 (0.0036)	0.0174*** (0.0039)	−0.0102*** (0.0016)	−0.0019 (0.0034)
Share of irrigation land	0.4912*** (0.0628)	−0.1499*** (0.0191)	−0.3532*** (0.0642)	0.4106*** (0.0602)	−0.1214*** (0.0193)	−0.3153*** (0.0634)	0.4627*** (0.0604)	−0.1508*** (0.0191)	−0.3418*** (0.0634)
Latitude	0.0347*** (0.0023)	−0.0006 (0.0008)	−0.0268*** (0.0020)	0.0315*** (0.0019)	0.0028*** (0.0008)	−0.0220*** (0.0017)	0.0357*** (0.0023)	−0.0011 (0.0008)	−0.0277*** (0.0020)
Time trend	0.0006 (0.0013)	0.0020*** (0.0004)	−0.0056*** (0.0014)	0.0033** (0.0013)	0.0011** (0.0005)	−0.0074*** (0.0015)	−0.0001 (0.0013)	0.0020*** (0.0004)	−0.0041*** (0.0013)
Long-term precipitation	0.0000 (0.0017)	−0.0109*** (0.0006)	−0.0192*** (0.0013)				0.0026 (0.0017)	−0.0104*** (0.0005)	−0.0223*** (0.0013)
Long-term degree-days	0.1613*** (0.0120)	−0.0462*** (0.0050)	−0.0645*** (0.0107)				0.1181*** (0.0108)	0.0077* (0.0040)	−0.0579*** (0.0093)
Long-term precipitation intensity index	−0.0342 (0.0569)	0.0046 (0.0208)	0.1140** (0.0511)				−0.4732*** (0.1173)	0.0415 (0.0391)	0.4942*** (0.1048)
Inter-annual precipitation	0.0020** (0.0008)	0.0005 (0.0003)	−0.0021*** (0.0007)	0.0059*** (0.0012)	−0.0077*** (0.0004)	−0.0164*** (0.0011)			
Inter-annual degree-days	−0.0517*** (0.0068)	0.0571*** (0.0032)	0.0126* (0.0066)	0.0873*** (0.0087)	0.0217*** (0.0037)	−0.0367*** (0.0077)			
Inter-annual precipitation intensity index	−0.0278 (0.0174)	−0.0351*** (0.0067)	0.0525*** (0.0156)	−0.0248 (0.0191)	0.0273*** (0.0074)	0.1591*** (0.0175)			
Drought index	−0.0103*** (0.0035)	−0.0156*** (0.0014)	−0.0031 (0.0030)	−0.0084** (0.0039)	−0.0230*** (0.0015)	−0.0183*** (0.0034)			
With-in-sample RMSE	0.1135	0.0555	0.1101	0.1161	0.0576	0.1130	0.1137	0.0562	0.1104
Out-of-sample RMSE	0.1183	0.0618	0.1116	0.1225	0.0634	0.1146	0.1197	0.0621	0.1124
Observations	15,926	15,926	15,926	15,926	15,926	15,926	15,926	15,926	15,926

Note: Dependent variables are agricultural land-use shares; panel clustered robust standard errors are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$, respectively.

(APEs) as well as the corresponding standard deviation at the sample mean for each variable. Table 2 shows the APEs to different agricultural land use systems from Eq. (1).

4.1. Estimated results

Considering results that are statistically significant, the consequences of changes in long-term climate characteristics are much larger determinants of the fate of cropland and grazing land than are those of inter-annual climate variability. Thus, we find that short-term phenomena simply do not have all that much of an effect except to the extent that they are harbinger of longer-term shifts, limited action is taken by farmers in the short period while make adaptations in the long term (Hsiang, 2016). This result also shows that future climate change could have a large influence on agriculture as it changes the climate normals and possibly also inter-annual climate variability because these two are correlated (Mendelsohn et al., 2007).

Focusing on the cumulative marginal effects of both inter-annual climate variability and long-term climate normals, Fig. 1 shows the non-linear relationship between predicted agricultural land use shares and changes in growing season degree-days and total precipitation. We find both hill-shape effects of degree-days and precipitation on predicted cropland use shares. As degree-days or precipitation goes up, cropland share increase to a certain threshold, around 4500 of degree-days and 120 cm of precipitation, and then declines. On the contrary, grazing land will benefit from the tail effects of lower or higher degree-days or precipitation. These results suggest that farmers adapt to hotter and dryer climate by changing the type of production system, from crop to livestock.

Average partial effects of extreme weather variables indicate a strong competition relationship among crop and grazing land uses. Both long-term and inter-annual precipitation intensity indices show that more precipitation variation is harmful for crop growing, causing more land is transferred to livestock grazing as is also found in Seo (2010) and Seo and Mendelsohn (2008). Similarly, we observe that more frequent drought occurrence exhibits a negative effect on crop and other cropland. These results suggest that crop production is vulnerable to extreme weather events (Schlenker and Roberts, 2006, 2009).

In addition, land use decisions respond to prices and costs of production as predicted by the economic theory. For example, cropland (grazing land) share increases when annualized crop (livestock) revenue-cost ratios increases or annualized livestock (crop) revenue-cost ratios decreases. Results in the first three columns of Table 2 also show that cropland share will increase and grazing land will decline when per acre government payments goes up. This is possibly due to government paid to raise farmer returns, which are generally only directing at cropping, so it leads to farmers utilizing more of their land in cropping relative to grazing. It is also argued by Annan and Schlenker (2015) that farmers already enrolled in crop insurance program do not have the incentive to engage in costly adaptation as insurance compensates them for potential loss from climate change, indicating that more crop insurance would bolster profitability and cause more land to be retained

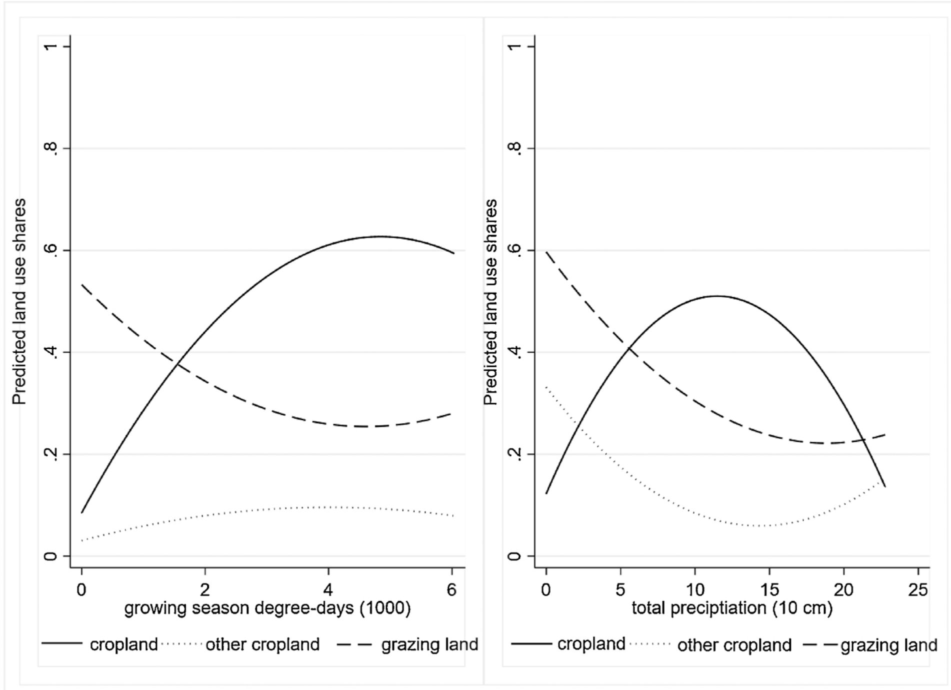

Fig. 1. Relationship between predicted land use shares and the cumulative effects of inter-annual and long-term climate variables.

in cropping.

We also find that increases in population density is encouraging substitution towards more intensive activities such as crop over livestock production. As expected, the model shows that an increase in irrigation share increases cropland use as water limitations are partly mitigated by irrigation technology plus there is inherent capital in delivering irrigation and this would make farmers more reluctant to abandon their investments to move to other land uses. In addition, the result on the latitude variable showing that cropland use is shifting to the north is found or suggested in many places including Adams et al. (1990); Reilly et al. (2003); Zilberman et al. (2004); Attavanich et al. (2013) and Mu et al. (2013).

4.2. Robustness checks

In Table 2, we also include results of alternative model specifications. Columns 4–6 show APEs from the regression only including variables of inter-annual climate variability and columns 7–9 show APEs from the regression only including variables of long-term climate normals. When comparing to results in columns 1–3, we find that coefficients of non-climatic variables having consistent signs and similar magnitudes. For coefficients of climate variables, there are some sign differences, which may due to the correlation between inter-annual climate variability and long-term climate normals.[7] However, as we could see in Fig. 1, the combined effects of inter-annual climate variability and long-term climate normals from Eq. (1) are as expected. These results indicate that an estimation approach that only consider long-term climate normals or only short-term climate characteristics may independently explain farm outcomes, as to some extent the shifts in the short-term phenomena are reflective of shifts in long-term phenomena because they are correlated with each other. However, it is important to include both in the same statistical model to get accurate measures of their individual contribution to farm land uses (Mendelsohn et al., 2007).

To test which of the three models fits data better, we apply the Wald test of the Eq. (1) and find that the joint test statistics (the chi-squared value) of annualized revenue-cost ratios, variables of long-term climate normals and inter-annual climate variability are 98.70, and 1701.80 and 549.57, respectively. Based on the p-value, we are able to reject the null hypothesis of that the estimated coefficients are jointly equal to zero at the 1% confidence level.

Because we rely on model estimates to predict land-use changes under various future climates, we also compare the with-in- and out-of-sample root mean squared error (RMSE) from three models and present results at the bottom of Table 2.[8] In general, Eq. (1) predicts slightly smaller with-in-sample and out-of-sample RMSEs. Thus, we choose Eq. (1) as the preferred model and use its estimates for later analysis.

As additional robustness check of Eq. (1), Table 3 shows the APEs using long-term climate normals over different periods, e.g., five-year, fifteen-year and thirty-year moving averages. It can be seen that results are consistent to those in the first three columns of Table 2 in terms of signs and magnitudes, suggesting that climate need not have a fundamental timescale and studies could use periods of varying lengths of time depending on the research design (Hsiang, 2016). Here, we use ten-year moving average to define long-term climate normals because it is a reasonable time scale for farmers to track their memory and to make actions (Burke and Emerick, 2016).

5. Future climate projections

Now we turn attention towards projecting the future land-use consequences of projected climate change. To do this, we use a suite of downscaled climate model projections from 20 climate-models that were used in the Coupled Model Intercomparison Project Phase 5

[7] Multi-collinearity could be an issue by including both the inter-annual climate variability and long-term climate normals as well as their squared terms. However, multi-collinearity does not reduce the predictive power or reliability of the model as a whole (Farrar and Glauber, 1967). More importantly, there is an increasing need to include all dimensions of climate conditions when examining climate change impacts (Hsiang, 2016).

[8] To get out-of-sample RMSE, we use data from seven Census of Agriculture and run the land-use model seven times to get the predicted land-use shares. We then calculate the average of the seven RMSEs.

Table 3
Robustness check using long-term climate normals over different periods of time.

Variables	Share of cropland			Share of marginal land			Share of grazing land		
	5-year	15-year	30-year	5-year	15-year	30-year	5-year	15-year	30-year
Annualized revenue-cost ratios of crop products	0.0088***	0.0093***	0.0086***	−0.0036***	−0.0036***	−0.0035***	−0.0034***	−0.0033***	−0.0032***
	(0.0011)	(0.0012)	(0.0011)	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0009)
Annualized revenue-cost ratios of livestock products	−0.0030	−0.0028	−0.0035	−0.0022***	−0.0022***	−0.0023***	0.0050	0.0054*	0.0059*
	(0.0028)	(0.0027)	(0.0025)	(0.0005)	(0.0005)	(0.0005)	(0.0034)	(0.0033)	(0.0031)
Annualized government payments	0.2886***	0.2721***	0.3601***	0.0193	0.0056	0.0136	−0.3676***	−0.3428***	−0.4500***
	(0.0901)	(0.0923)	(0.0909)	(0.0231)	(0.0230)	(0.0232)	(0.1017)	(0.1022)	(0.1017)
Population density	0.0157***	0.0167***	0.0169***	−0.0100***	−0.0097***	−0.0101***	−0.0019	−0.0018	−0.0021
	(0.0038)	(0.0039)	(0.0039)	(0.0015)	(0.0016)	(0.0016)	(0.0034)	(0.0034)	(0.0034)
Share of irrigation land	0.4691***	0.4732***	0.4519***	−0.1442***	−0.1451***	−0.1399***	−0.3487***	−0.3403***	−0.3306***
	(0.0618)	(0.0625)	(0.0609)	(0.0191)	(0.0191)	(0.0189)	(0.0641)	(0.0637)	(0.0631)
Latitude	0.0339***	0.0341***	0.0351***	0.0001	−0.0003	−0.0007	−0.0258***	−0.0268***	−0.0278***
	(0.0022)	(0.0023)	(0.0023)	(0.0008)	(0.0008)	(0.0008)	(0.0019)	(0.0020)	(0.0020)
Time trend	0.0007	0.0001	0.0001	0.0022***	0.0018***	0.0020***	−0.0057***	−0.0052***	−0.0042***
	(0.0013)	(0.0013)	(0.0012)	(0.0004)	(0.0004)	(0.0004)	(0.0014)	(0.0014)	(0.0014)
Long-term precipitation	−0.0007	−0.0014	−0.0014	−0.0082***	−0.0100***	−0.0105***	−0.0164***	−0.0193***	−0.0210***
	(0.0014)	(0.0017)	(0.0018)	(0.0005)	(0.0005)	(0.0006)	(0.0012)	(0.0014)	(0.0014)
Long-term degree-days	0.1591***	0.1435***	0.1660***	−0.0455***	−0.0362***	−0.0441***	−0.0603***	−0.0567***	−0.0659***
	(0.0132)	(0.0123)	(0.0126)	(0.0057)	(0.0052)	(0.0055)	(0.0119)	(0.0109)	(0.0111)
Long-term precipitation intensity index	−0.0633*	−0.0716	−0.4362***	−0.0247*	−0.0436*	0.0381	0.0588*	0.1616**	0.4745***
	(0.0365)	(0.0736)	(0.1161)	(0.0140)	(0.0256)	(0.0390)	(0.0327)	(0.0656)	(0.1036)
Inter-annual precipitation	0.0026***	0.0031***	0.0035***	−0.0015***	−0.0001	0.0001	−0.0043***	−0.0021***	−0.0011
	(0.0008)	(0.0008)	(0.0009)	(0.0003)	(0.0003)	(0.0004)	(0.0007)	(0.0007)	(0.0008)
Inter-annual degree-days	−0.0538***	−0.0359***	−0.0484***	0.0582***	0.0493***	0.0540***	0.0120	0.0049	0.0070
	(0.0082)	(0.0071)	(0.0074)	(0.0040)	(0.0033)	(0.0036)	(0.0079)	(0.0066)	(0.0069)
Inter-annual precipitation intensity index	−0.0414**	−0.0356**	−0.0378**	−0.0144**	−0.0283***	−0.0323***	0.0728***	0.0528***	0.0371**
	(0.0175)	(0.0174)	(0.0179)	(0.0067)	(0.0067)	(0.0068)	(0.0158)	(0.0157)	(0.0161)
Drought index	−0.0085**	−0.0113***	−0.0097***	−0.0192***	−0.0160***	−0.0152***	−0.0084***	−0.0028	0.0007
	(0.0036)	(0.0035)	(0.0035)	(0.0014)	(0.0014)	(0.0014)	(0.0030)	(0.0030)	(0.0030)
With-in-sample RMSE	0.1161	0.1135	0.1129	0.0558	0.0556	0.0556	0.1106	0.1101	0.1097
Out-of-sample RMSE	0.1225	0.1196	0.1183	0.0631	0.0621	0.0622	0.1135	0.1127	0.1120
Observations	15,926	15,926	15,926	15,926	15,926	15,926	15,926	15,926	15,926

Note: dependent variables are agricultural land-use shares; panel clustered robust standard errors are reported in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$, respectively.

(CMIP5). We will do this for two Representative Concentration Pathways (RCPs)[9], namely RCP4.5 and RCP8.5. Across these model runs under the RCP4.5 scenario, there is a projected global temperature increase of 1.4 to 1.8 °C by the end of this century. In turn, runs under the RCP8.5 scenario result in a larger temperature increase for the same time horizon amounting to 2.0 to 3.7 °C (Van Vuuren et al., 2011). To use the CMIP5 projections, we used versions of them downscaled to a ~4-km resolution that were developed by Abatzoglou and Brown (2012). Degree-days and precipitation intensity index were then calculated following the same procedure as previously mentioned. Evaluations of the downscaled data of all 20 climate models show projected substantial warming across the United States, whereas changes in precipitation are more uncertain and exhibit large geographic differences (Maloney et al., 2014).

To predict land use share change under future climate projections, we first predict a baseline land use using climate data from 1976 to 2005 and then project land use shifts to the end of the 21st century using the individual downscaled climate projections. In doing this, we hold all other non-weather and climate variables at their sample means during the period from 1976 to 2005. We then compute the percent changes from the baseline for the time periods covering 2010 to 2039 (labeled 2025), 2040 to 2069 (labeled 2055), and 2070 to 2099 (labeled 2085). Regardless of the uncertainty from climate models and RCPs, we find the projected crop land share will increase and grazing land share will decrease from labeled 2025 to labeled 2085, with the average change of the former from 5% to 15% and the latter from −4% to −10%. For the same time horizons, changes in other non-grazing uses of cropland are neglectable.

As also found in numerous places including Mu et al. (2017), changes in land use share under future climate are heterogeneous across space, time, climate model and RCP. The spatial pattern in Fig. 2 (first and second columns) shows that cropland share increases across the northern and interior western United States, and grazing land share increases in southern regions and counties in the Pacific Northwest. These results are consistent to previous studies and suggest that crop production is shifting to the north as climate changes (Adams et al., 1990; Attavanich et al., 2013; Mu et al., 2013; Reilly et al., 2003; Zilberman et al., 2004). The possible reason is that future climate with higher temperature and longer degree-days will be beneficial for crop production in regions that are currently limited by colder conditions during the growing season. Whereas more land is used for livestock grazing in the south as crops are more limited by hotter conditions and livestock are more heat-tolerant than crop under the warming climate (Seo et al., 2010; Seo and Mendelsohn, 2008).

Fig. 2 (different rows) also shows land use change adaptation as it evolves over time. In the most distant future, cropland share increases more in the northern regions and decreases more in the southern areas, whereas grazing land share decreases more in northern regions and increases more in the southern areas (Cho and McCarl, 2017; Fei et al., 2017; Mu et al., 2017). These results indicate that the substitution effects between crop production and livestock grazing becomes stronger as the climate gets warmer in the late period of the 21st century and this situation becomes even worse under RCP8.5 which projects much higher increase in global mean temperature.

To show uncertainty from climate models and RCPs, Fig. 3 presents percent changes of predicted agricultural land use shares across three time horizons for two RCPs. Each box in Fig. 3 indicates the variation

[9] Representative Concentration Pathways (RCPs) are four greenhouse gas concentration (not emissions) trajectories adopted by the Intergovernmental Panel on Climate Change (IPCC) for its fifth Assessment Report (AR5) in 2014. The four RCPs, RCP2.6, RCP4.5, RCP6, and RCP8.5, are named after a possible range of radiative forcing values in the year 2100 relative to pre-industrial values (+2.6, +4.5, +6.0, and +8.5 W/m^2, respectively).

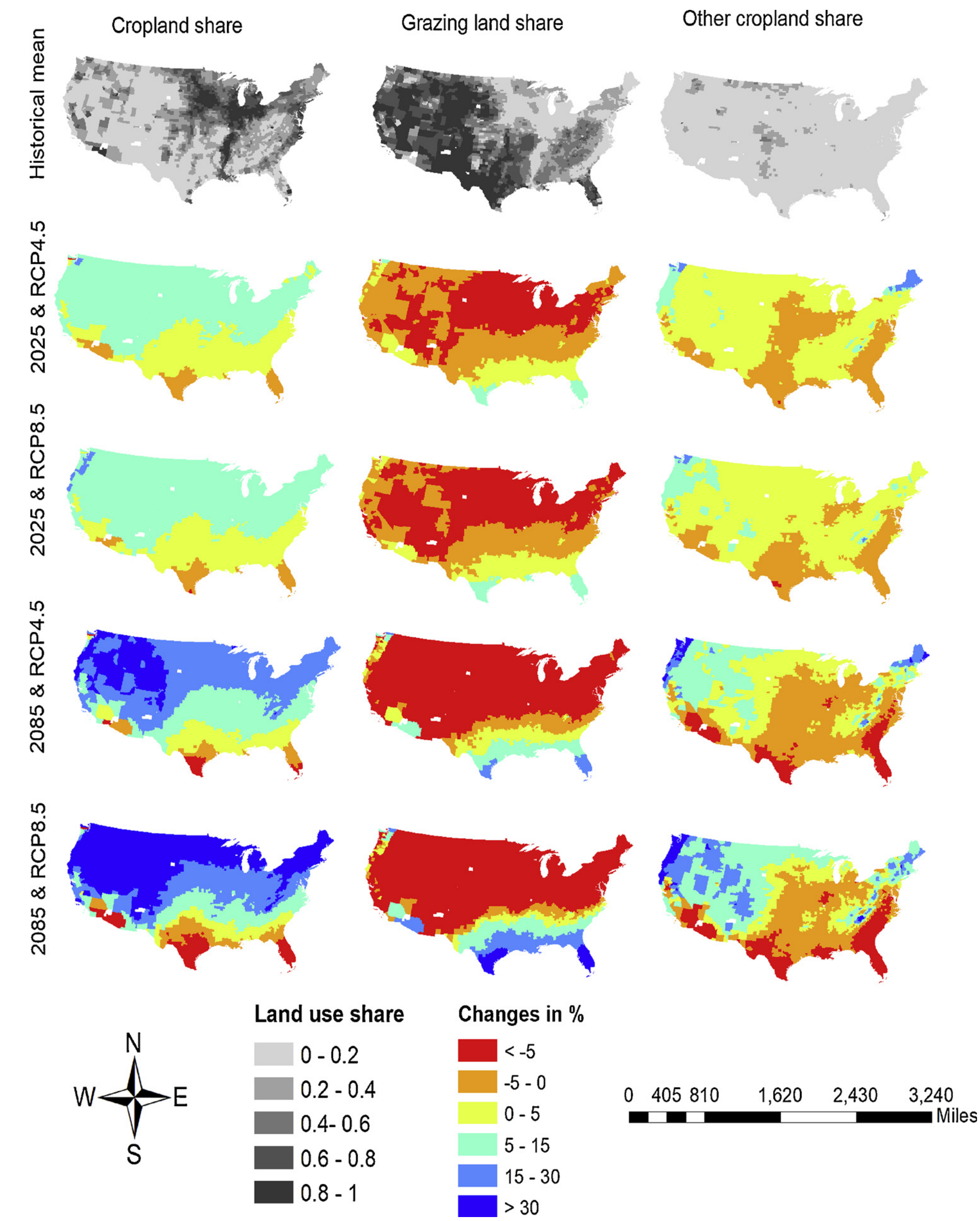

Fig. 2. Historical mean land use shares and predicted percent changes under future climate projections for two time horizons and two RCPs.
Note: predicted changes of land use shares were aggregated across 20 climate models.

from the 25% to the 75% percentile of the predicted values across 20 climate models and the lower and upper bars show the minimum and maximum values, respectively. Fig. 3 shows that predicted changes of a particular land use share exhibit large variation within RCP scenario due to the different climate model projections. This variation increases along with the increase in time horizon and RCP. Specifically, in the early period of the 21st century, changes in land use shares are predicted to be small and the difference between the lower and higher RCPs is small, which is not at all surprising given the small disparity in climate change projections. However, in the later period, changes in land use shares are much more distinct and larger due to a larger range of variation in projected extent of climate change. In addition, the difference between the lower and higher RCPs is much more substantial due to the much greater variation between the projected magnitudes of climate change.

6. Policy implications

Investigating agricultural land use change under future climate change has important policy implications. First, understanding the climate change adaptation potential via land use change may help to better understand the opportunity and challenges for global food security and food system (Brown et al., 2017). On the one hand, global demand for food is expected to increase because of population expansion and a shift towards a more "westernized" diet in developing regions (Tai et al., 2014). On the other hand, changes in regional climates threaten agricultural production and increase the vulnerability of people dependent on agriculture (Lipper et al., 2014). Therefore, there is a risk associated with food availability and stability (Butt et al., 2005). One approach to reorient agricultural systems to support food security is to increase the adaptive capacity of farmers as well as increase resilience and resource use efficiency in agricultural production systems. In this regard, adaptation through land use change is one of those approaches that can be promoted by policymakers towards a

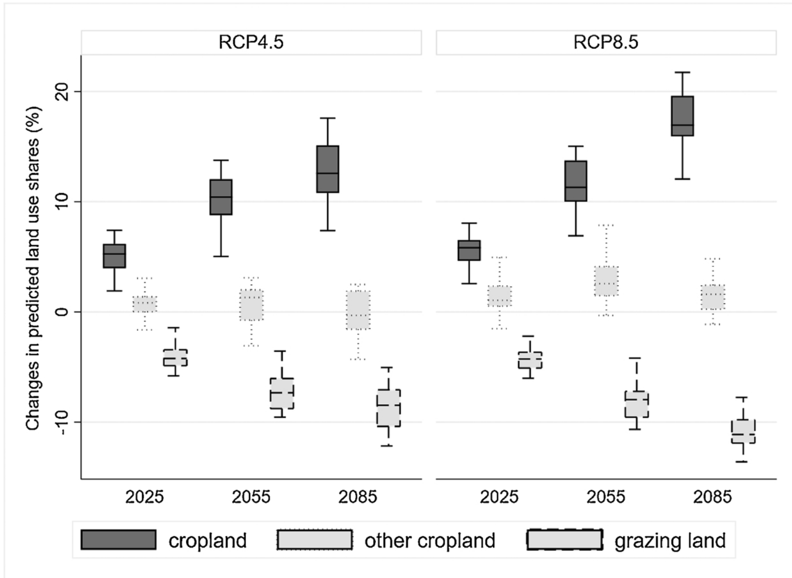

Fig. 3. Predicted percent change in agricultural land use shares for three time horizons and two RCPs.
Note: each box shows the variation of predicted values over 20 climate models.

better climate-resilient pathway (Lipper et al., 2014).

Second, changes in cropping systems to adapt to climate change may cause potential negative or positive impacts to ecosystems, including the provision of wildlife habitat, changes in water and air quality, and changes in animal and plant species (Attavanich et al., 2014; Lawler et al., 2014). Thus, knowing the status of future land use change at the local level may provide better information to regional or local ecosystem management. More importantly, it may help in the discussion of making alternative incentive policies that could be used to mitigate the possible negative impacts and to enhance benefits caused by land use change on the provision of ecosystem services (Lawler et al., 2014).

Third, changes in agricultural land may need more future infrastructure supports (Attavanich et al., 2013). With predicted increase in cropland in northern regions, there is an increasing need of navigation networks, such as roads, railways, locks, dams or storage facilities due to climate-induced shift in crop mix. Therefore, policies promoting the assessment of maintaining the conditions of current navigation systems or developing new infrastructure will become an emerging research area. If policies prefer slowing the climate-induced shift in crop and livestock production, there will be a need for more funding supports to develop and introduce new varieties that are more heat-tolerant and cost-effective under future climate change (Zhang et al., 2013).

7. Conclusion

In this paper, we examine adaptation responses to climate change through the adjustment of agricultural land use. Using county level data from Census of Agriculture over 1982 to 2012 in the Contiguous United States, this paper finds that the effects of long-term climate normals are generally as important as that of short-term climate variability, suggesting that projected changes in climate in the future may play an significant role in shaping agricultural land uses over the 21st century.

Under future climate, results from this paper show substantial potential for adaptation to climate change, as other studies have also shown. Future predictions using 20 climate model projections show that an expansion of cropland share across the northern and interior western United States with the increase of grazing land share in southern regions and Inland Pacific Northwest. However, to which extent the adaptation potential would be is dependent on the climate model, RCP and time horizon under consideration. Even within counties where a net economic gain is predicted, a proportion of farmers are still vulnerable to climate change due to the heterogeneity of economic and climate conditions within the county (Antle et al., 2018).

In this paper, we focus on land use change within the agriculture sector. However, climate may affect forest and urban land uses as well (Albouy et al., 2016; Keenan, 2015). These may lead to converting land from agricultural production or deforestation to urban uses (Bigelow et al., 2017). Given the different mechanisms for changes in land use development, such as economic development, increase in per capita income as well as changes in immigration patterns, there is a need to examine the land use change in a broader uses under climate change. Moreover, this paper does not consider market risk coming from changes in prices and costs when predicting the future status of agricultural land use. Including projections of future socio-economic scenarios could make large difference of climate impacts as well as farmer's adaptation behavior (Antle et al., 2017). However, this analysis is beyond the scope of this paper and could be developed for future research.

Results in this paper are also limited to the fact that effects of carbon dioxide fertilization are not taken into account although we controlled soil conditions in the analysis (Attavanich and McCarl, 2014). Urban et al. (2015) suggested that elevated carbon dioxide significantly reduces maize yield variability and net damages from climate change will become larger than that without considering carbon dioxide fertilization. Different from previous studies that focus on crop productivity, the effects of carbon dioxide fertilization are indirect when examining land uses, but it is still interesting to see how that will affect farmers' decisions on land use allocation.

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Appendix A

. **Table A1**
Estimated coefficients of the Fractional Multinomial Logit model using 10-year moving average climate normal.

	Share of marginal land	Share of cropland	Share of marginal land
Annualized revenue-cost ratios of crop products	0.042***	−0.016	0.013
	(0.008)	(0.012)	(0.008)
Annualized revenue-cost ratios of livestock products	−0.000	−0.019***	0.024*
	(0.005)	(0.006)	(0.014)
Annualized government payments	−0.433	−0.988**	−2.078***
	(0.389)	(0.413)	(0.528)
Population density	0.086***	−0.064***	0.042**
	(0.020)	(0.022)	(0.021)
Population density, squared	−0.004***	−0.000	−0.000
	(0.001)	(0.000)	(0.001)
Share of irrigation	0.852***	−1.817***	−1.314***
	(0.305)	(0.323)	(0.356)
Latitude	0.135***	0.060***	−0.024*
	(0.015)	(0.016)	(0.015)
Time trend	−0.027***	−0.006	−0.048***
	(0.005)	(0.006)	(0.007)
Long-term precipitation	−0.637***	−1.051***	−0.897***
	(0.065)	(0.077)	(0.071)
Long-term precipitation, squared	0.018***	0.032***	0.027***
	(0.003)	(0.003)	(0.003)
Long-term degree-days	0.916***	−0.306	0.060
	(0.194)	(0.228)	(0.232)
Long-term degree-days, squared	−0.025	0.047	0.035
	(0.033)	(0.036)	(0.038)
Long-term precipitation intensity index	0.714*	0.834**	1.170***
	(0.365)	(0.382)	(0.377)
Inter-annual precipitation	−0.002	−0.011	−0.019
	(0.016)	(0.018)	(0.016)
Inter-annual precipitation, squared	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Inter-annual degree-days	0.265*	1.271***	0.132
	(0.140)	(0.168)	(0.168)
Inter-annual degree-days, squared	−0.037	−0.084***	0.014
	(0.023)	(0.027)	(0.028)
Inter-annual precipitation intensity index	−0.151	−0.497***	0.082
	(0.100)	(0.115)	(0.099)
Drought	−0.057**	−0.254***	−0.087***
	(0.022)	(0.024)	(0.021)
Fraction clay	0.756***	0.364***	0.772***
	(0.120)	(0.114)	(0.120)
Fraction sand	0.034	0.339*	−0.119
	(0.154)	(0.179)	(0.165)
Fraction flood-prone	−0.163	−0.471***	0.165
	(0.120)	(0.117)	(0.112)
K-Fact	1.399**	2.316***	1.656***
	(0.557)	(0.626)	(0.597)
Slop length	0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)
Permeability	−0.017	−0.055***	−0.020
	(0.017)	(0.019)	(0.018)
Wetlands	−1.004***	−0.628***	−2.192***
	(0.214)	(0.203)	(0.207)
Moisture capacity	7.868***	5.065***	3.002**
	(1.149)	(1.206)	(1.225)
Salinity	5.321***	3.644***	5.411***
	(1.030)	(1.101)	(1.089)
Constant	−4.456***	0.627	7.243***
	(0.792)	(0.874)	(0.777)
N	15,926		

Note: Dependent variables are agricultural land-use shares; panel clustered robust standard errors are reported in parentheses; *$p < 0.1$; ** $p < 0.05$; *** $p < 0.01$, respectively.

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